Schooling, Experience, Career Interruptions, and Earnings

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Abstract

This paper investigates whether the returns to work experience vary with education. Different from existing literature, I distinguish the returns to actual experience from the returns to potential experience. While I find that returns to potential experience do not vary across education groups, I estimate that more educated workers have a higher wage increase with actual experience. This result is not explained by known sources of potential experience bias, as more educated workers have higher employment attachment throughout their careers. In order to rationalize these findings, I discuss a new source of potential experience bias generated by wage losses after non-working periods. Indeed, I find evidence that more educated workers suffer higher wage losses after periods of unemployment. This result explains the greater downward bias of potential experience for more educated workers.

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1 Introduction

Economists have long recognized that schooling and experience are two of the most important aspects of earnings determination.[1] Given the importance of these two variables, a natural question is how does their interaction affect earnings? In other words, do educated workers have a higher or lower wage increase as they accumulate experience? It is within this context that this paper examines how the returns to work experience change across educational groups. In contrast to a typical Mincerian wage model, I take into consideration that workers spend a significant amount of time not employed throughout their careers in the estimation on how the returns to experience change across educational groups.

While considering the difference between working and non-working periods in the construction of the experience variable seems natural, this difference has been ignored in the literature that studies how the returns to experience change across educational groups. Table 1 presents some the most important papers that have addressed this question. As can be seen in the table, in order to identify whether more educated workers have a higher or lower wage increase with experience, these papers have used rough measures of experience, such as age minus schooling minus six or years since transition to the labor force.[2]

The overall finding in the literature is that returns to potential experience *do not vary* across educational groups in old datasets (Mincer, 1974), or *decrease* with education in the most recent datasets (Lemieux, 2006 and Heckman et al., 2006).[3] These results had a lasting influence on empirical work in the field of labor economics. For example, Mincer (1974) used his findings to justify the separability between schooling and experience present in the Mincer earnings equation, which has remained for decades the "workhorse" of empirical research on earnings determination.[4]

[1] The study of the impact of schooling and experience on earnings goes back to Becker (1962), Mincer (1962) and Ben-Porath (1967).

[2] Note also that these studies differ on how they define earnings. For example, Farber and Gibbons (1996) use earning in levels. There is also a difference between using annual or hourly wages as the dependent variable. Mincer (1974) uses annual earnings, but only finds evidence for parallel wage profile when controlling for weeks worked in the past calendar year. With the exception of Heckman et al. (2006), most recent papers have used hourly earnings as the dependent variable.

[3] Altonji and Pierret (2001) also find negative coefficients for interaction between schooling and experience when including ability measures and its interaction with experience on the earnings equation.

[4] Mincer proposes that all workers have the same rate of returns to on-the-job investment, that is independent of

Farber and Gibbons (1996), and Altonji and Pierret (2001) used their empirical results to justify that employers use schooling as a signal of a worker's ability.

Despite the unquestionable value of the articles presented in table 1, in this paper I point out issues associated with the measures of experience they use. Indeed, the first contribution of this paper is to discuss the bias associated with the potential experience measure used in Mincer (1974), Altonji and Pierret (2001), Lemieux (2006) and Heckman et al. (2006). I demonstrate that if educated workers suffer greater wage losses after periods of unemployment, potential experience can produce greater bias to the returns to experience for more educated workers.

This source of bias associated with using potential experience variable is at odds with current literature (Filer, 1993, Altonji and Blank, 1999, and Blau and Kahn, 2013). According to these studies, potential experience generates *lower* bias to the returns to experience for demographic groups with higher employment attachment, such as more educated workers. In contrast, I demonstrate that potential experience can generate a *greater* bias to the returns to experience for workers with higher employment attachment, if their earnings suffer higher drops after career interruptions. To my knowledge, this is the first paper that addresses this source of bias which might have affected many studies that estimate earnings equation with potential experience variable.

To show the importance of using accurate measures of experience, I use the 1979 wave of National Longitudinal Survey of Youth (NLSY79) to estimate how the returns to actual and potential experience change with schooling. In accordance with past studies, I find that returns to potential experience do not vary with education. However, the results using accurate measures of work experience are remarkably different from those in existing studies. Using different specifications of the wage equation, I consistently find that more educated workers have a higher wage increase with actual experience. In addition, I estimate model where earnings also depend on past unemployment and non-participation periods. This estimation shows evidence that more educated workers suffer a higher wage drop after periods of unemployment. This result explains the greater downward bias generated by the potential experience variable for highly educated workers.

their educational achievement. This independence between human capital investments at school and on-the-job can justify the parallel log earnings-experience profiles across educational groups.

I provide several robustness checks for these empirical results. First, I estimate a non-parametric model where I do not impose restrictions on the relation between earnings, schooling, work experience, and career interruptions. Second, I change the earnings model so that the timing of career interruptions can also change the effect of schooling on earnings. Third, I estimate a model using an individual fixed effect assumption. In all these specifications, I consistently find that more educated workers have a higher wage increase with work experience and suffer greater wage losses after periods of unemployment.

Given the novelty of these results, I propose a simple two period model that can explain the empirical findings of this paper. The model is based on theories of on-the-job training and layoffs decisions under asymmetric information, as presented in Acemoglu and Pischke (1998) and Gibbons and Katz (1991). In the model, firms have greater returns to training high ability workers. I extend this type of models by allowing firms to use information on worker's education to predict unobservable ability when making training decisions in the first period. In the model, educated workers receive more on-the-job training because they are more likely to be high ability. In the second period, current employer learns a worker's ability and makes layoff decision. Employers are more surprised by the revelation that an educated worker is low ability and therefore educated workers suffer a higher wage loss after being laid-off.

The paper is organized as follows. In section 2, I discuss the issues of using potential experience when estimating a typical Mincer equation if career interruptions have an impact on earnings. In section 3, I describe the data and I show some descriptive statistics. Section 4 presents the main empirical results of the paper, and I provide some robustness checks. In section 5, I present an extended discussion on how to conciliate the empirical results of this paper with existing theory of wage determination. In section 6, I conclude the paper and present a research agenda.

2 Potential Experience Bias in the Mincer Equation

The Mincer earnings equation has long been long used as the workhorse of empirical research on earnings determination. Based on theoretical and empirical arguments, Mincer (1974) proposed a specification where the logarithm of earnings is a linear function of education and a quadratic function of potential experience (age minus schooling minus six). Mincer also suggested that schooling and experience are separable in the earnings equation, meaning no interaction term between these two variables is required in the earnings equation. Notably, as discussed shown in table 1, Mincer founds evidence that potential experience profiles are nearly parallel across educational groups.

There is wide discussion on the potential pitfalls with the earnings specification proposed by Mincer (Murphy and Welch 1990 and Heckman et al. 2006), including discussion of the issues associated with using the potential experience variable (Filer, 1993 and Blau and Kahn, 2013). In addition to the existing critiques, in this section I discuss issues with using the potential experience variable when non-working periods affect earnings.

I begin the analysis with the traditional case where earnings are affected only by actual experience and not by non-working periods.[5] The log-earnings generating process of worker i at time period t ($\ln w_{it}$) with level of schooling s is defined by the equation below. The parameter β_1^s identifies the impact of the increase of actual experience for workers with level of education s.

$$\ln w_{it} = \beta_0^s + \beta_1^s exper_{it} + \varepsilon_{it} \tag{1}$$

For expositional purposes, and different from Mincer's suggested specification, I assume that log earnings are a linear function of experience. As discussed in Regan and Oaxaca (2009), an inclusion of a quadratic and cubic term tends to exacerbate the type of bias that is discussed here.[6]

The object of interest of the paper is the interaction between schooling and experience. In terms of the equation above, I am interested in how the parameter β_1^s changes across different educational groups. Note that according to Mincer (1974) original specification, log-experience profiles are parallel across educational groups: $\beta_1^s = \beta_1$ for all s.

Equation (1) describes how log-earnings changes with actual experience, but individuals can spend some time not working after they leave school. I define $l_{\tau i}$ as an indicator variable that

[5] In Mincer (1974), the potential experience variable is interpreted as a measure of on-the-job training.

[6] In the empirical section of the paper I include different functional forms for both actual experience and career interruptions.

assumes a value of one if individual i worked at past time period τ. The actual experience variable is defined by the sum of past working periods after a worker left school:

$$exper_{it} = \sum_{\tau=g}^{t-1} l_{i\tau}$$

where g is the time at which an individual leaves school. I also assume that $l_{i\tau}$ is independent of the wage error term ε_{it} and $\mathbb{E}[l_{i\tau}] = p_s$, where p_s is a constant between zero and one that indicates the expected fraction of periods that a worker with s level of education stays employed after leaving school.

In most datasets it is not possible to identify an individual's work history. For this reason, researchers have long used rough measures of experience which do not distinguish working and non-working periods, such as the potential experience variable. In the context described above, the potential experience variable $pexp_{it}$, is defined as the time period since an individual left school:[7]

$$pexp_{it} = t - 1 - g$$

In this framework, it is easy to show that the coefficient that expresses how earnings change with potential experience is a biased estimator of β_1^s, such that $\widetilde{\beta}_{pex} = p_s\beta_1^s$. In fact, this is typical attenuation bias associate with using the potential experience variable present in the literature (Filer, 1993 and Blau and Kahn, 2013). Note that while potential experience attenuates the returns to experience for all demographic groups, the attenuation bias is higher for demographic groups with lower employment attachment. That is the reason why using complete measures of actual experience is a special issue in the literature that studies the gender wage gap (Altonji and Blank, 1999).

Note that as educated workers tend to have a higher employment attachment than uneducated workers, such that $p_s > p_{s-1}$, this model predicts that potential experience underestimates the difference in the wage growth between educated and uneducated workers. In other words, if earnings are not affected by career interruptions, the potential experience generates a lower bias to the returns

[7] Mincer (1974)'s definition of age-6-schooling would also generate an error term regarding the correct measure of the time a worker left school. For simplicity, I will assume this term is orthogonal to all other variables of the model, and therefore, I ignore it here.

to experience for more educated workers. However, as I will show in section 3.2, this is the opposite to what it is observed in the data.

Suppose now that in addition to actual experience, non-working periods also have a long-term impact on wages.[8] A representation for the earnings equation in this framework would be:

$$\ln w_{it} = \beta_0^s + \beta_1^s exper_{it} + \beta_2^s interr_{it} + \varepsilon_{it} \tag{2}$$

where $inter_{it}$ is a measure of career interruptions of a worker since leaving school. Using the same notation as before, I define career interruptions as the accumulation of non-working periods since an individual left school:

$$interr_{it} = \sum_{\tau=g}^{t-1}(1 - l_{i\tau})$$

Note that for simplicity, I assume that earnings are affected by the cumulative non-working periods. However, one can argue that the order and length of non-working periods have a different impact on earnings (Light and Ureta, 1995). In the empirical sections of the paper I also consider this possibility, but for exposition I assume that earnings are only affected by the accumulation of out-of work periods (Albrecht et al., 1999).

Under the earnings generating process described in (2), it is easy to show that a regression of earnings on potential experience identifies the following object:

$$\widetilde{\beta}_{pex}^s = p_s\beta_1^s + (1 - p_s)\beta_2^s$$

Note that in this framework $\widetilde{\beta}_{pex}^s$ confounds the effect of actual experience and career interruptions on earnings. In precise terms, the potential experience effect on earnings is a weighted average of β_1^s and β_2^s, with the weight being defined as the expected employment attachment of workers.

A few comments are needed on how this framework is related to the traditional potential experience bias, as presented in the discussion of model (1). First, if career interruptions have a negative

[8]Possible explanations for that are human capital depreciation (Mincer and Polachek, 1974 and Mincer and Ofek, 1982), firms using the information on past non-working periods as a signal of a worker's productivity (Albrecht et al., 1999), or even that workers accept a wage loss after career interruptions due to liquidity constraints, end of non-working benefits or disutility from leisure (Arulampalam, 2001). In section 4, I present a theory for why career interruptions affect wages.

impact on earnings ($\beta_2^s < 0$), the downward bias on estimating on the returns to actual experience is even greater than what the literature has been suggested (Filer, 1993 and Blau and Kahn, 2013).

Second, the potential experience bias can cause greater bias for groups with higher employment attachment. If demographic groups with high employment attachment are also more affected by career interruption (more negative β_2^s), it might be the case that $\widetilde{\beta}_{pex}^s$ is a more biased estimator of β_1^s than it is for groups with low employment attachment. In section 3.2 I demonstrate that i) educated workers have a higher employment attachment; ii) educated workers face much greater wage losses with career interruptions; and iii) potential experience produces a greater bias to the returns to actual experience for more educated workers.

3 Empirical Dynamics

3.1 Data

The data used in this paper are the 1979-2010 waves of the National Longitudinal Survey of Youth (NLSY) 1979. The NLSY is well suited for this study because it contains detailed information about individuals' work history since an early age, and follows them during a significant portion of their careers. The individuals in the sample were 14–22 years old when they were first surveyed in 1979, and they were surveyed annually from to 1979 to 1993 and biennially from 1994 to 2010.

The sample is restricted to the 2,657 non-black males from the cross-section (nationally representative) sample. This decision to restrict the sample was based on several reasons. First, this is a more stable demographic group during the decades of analysis. The labor market for women and African Americans has passed through significant changes in the past 30 years. Second, reasons for career interruptions might differ by gender and race. Even though it is possible to differentiate unemployment from out-of-the-labor-force periods in the data, it is well know that reasons for non-participation in the labor market can substantially differ among demographic groups. Finally, most of the current studies presented in table 1 restrict the sample to non-black males, consequently this sample restriction allows a better comparison between my results and previous studies.

Nevertheless, I also present the main results of the paper for these groups, separately.

I define "year of leaving school" as the year when a worker has achieved his highest schooling level and I consider only workers that have been in the labor market after they left school.[9] Note that this definition for year of leaving school assures that career interruptions are not caused by a worker's decision to go back to school. However, it also ignores work experience that an individual might have accumulated before achieving his highest degree level. In order to show that the main findings of the paper are not sensitive to such previous work experiences, I also present robustness checks where I define "year of leaving school" as the year an individual reports to not be enrolled in school for the first time.

In the NLSY it is possible to identify week-by-week records of individuals' labor force status since 1978. I use these variables to calculate for each potential experience year (age minus schooling minus six) the share of weeks that each worker in the sample spent working, unemployed, out of the labor force, or in active military service. I use this information to present statistics on average employment attachment over the life cycle for high school graduates and workers with at least a college degree in figures 1 and 2, respectively. These figures reveal that both high school and college graduates spend on average a significant share of their time not working after leaving school, although career interruptions happen much more often for the former group.

A surprising finding from these figures is that non-black males spend a significant share of their time out-of-the labor force throughout their careers. Although the NLSY provides limited information on the reasons for non-participation of workers, I did some further investigation of the available data for why these groups of workers are out-of-the labor force.[10] The results show that the reasons are very diverse, with the three most common reasons being individuals that did not want to work (20%), had a new job they were to start (19%) and were ill or unable to work (14%).

In addition to week-by-week information, NLSY also provides information on weeks between interview years that an individual spent working, unemployed, out of the labor force, or in military

[9] I dropped 75 individuals that did not have any observations after the year they left school.

[10] The data is limited due to the changes of questionnaires across years. These statistics are based on the years 1989-1993, when the most complete questionnaires on the reasons for non-participation are available.

service [11] These retrospective variables were used to construct the main work history variables used in the paper, as presented in table 2. More specifically, for each individual, work experience is defined as the cumulative number of weeks spent working since leaving school. In addition, cumulative unemployment, OLF, and military service years were defined as the number of weeks spent in each of these labor force conditions since leaving school. I then divide all variables by 52, so that the measurement unit is year.[12] Throughout the paper, potential experience is defined as age minus schooling minus six. This is the variable typically used in the literature (table 1) to measure experience, and as discussed before, it does not distinguish working and non-working periods throughout a worker's career. Note that because some individuals take more time to finish school than their schooling years, potential experience does not accurately measure the years a worker is in the labor market. For this reason, I also use time since leaving school as an alternative measure of experience that does not account for non-working periods. Note that time since leaving school is just the sum of the other cumulative work history variables.[13]

The wage is calculated as the hourly rate of pay (measured in year 1999 dollars) for the current or most recent job of a worker.[14] In order to perform the earnings equation estimation, I also restrict the observations to individuals employed at time of interview who work for hourly wages higher than $1 and less $100.[15] After these sample restrictions given above, the remaining sample consists of 2,484 individuals with 33,707 observations. All the statistics in the paper are unweighted.

Table 3 contains the main statistics of the sample used in the earnings equation estimations for

[11] There is also information on the percentage of weeks that NLSY cannot be accounted for. I use this information as a control in all regressions.

[12] In section 3.2.3 I also explore the possibility that timing of career interruptions might affect earnings.

[13] An issue I faced while creating the work history variables is the fact that 7% of the individuals in the sample graduated before 1978 and there is no available information regarding their work history before this year. I try to overcome this problem by using information available on when a worker left school (a year before 1978) and impute the work history variables described in table 2 for these individuals, between the year of leaving school and the year 1978. The imputation method consists of calculating the number of work/unemployment/OLF/military service weeks for the 1978 calendar year, and the assumption that it was constant between the year of leaving school and 1978. An alternative approach is to drop the 196 individuals who graduated before 1978 from the analysis. The results of this second approach are quite similar to imputing the work history variable, so I decided to omit them in this paper, but they are available upon request.

[14] The hourly rate of pay is calculated in the NLSY from answers to questions concerning earnings and time units for pay. If a respondent reports wages with an hourly time unit, actual responses are reported as the hourly rate of pay. For those reporting a different time unit, NLSY uses number of hours usually worked per week to calculate an hourly rate of pay.

[15] There are 41 individuals who do not have any observations during the whole period of analysis with earnings within this interval.

different educational levels. This table highlights some important features of the data. First, the mean of the potential experience and time since leaving school variables are significantly greater than the mean of the work experience for all educational groups. This shows that even for non-black males – a group with considerably higher employment attachment – potential experience substantially overstates actual experience. However, as expected, the difference is higher for less educated workers. Second, the individuals in all the educational groups spend more time out of the labor force than unemployed throughout their career. Finally, the work history information reported in the NLSY is quite accurate: for only 0.8% of weeks since leaving school NLSY was not able to define the labor status of the workers in the sample.

3.2 Earnings Dynamics Estimation

The first model estimated in this paper represents the typical Mincerian earnings equation that has been widely used in the literature, which shows how the effect of schooling on wages changes with potential experience (see table 1). I refer to this model as the traditional model and define log-earnings of individual i in time period t as:

$$\ln w_{it} = \alpha_0 + \alpha_1 s_i + \alpha_2 (s_i \times pexp_{it}) + g(pexp_{it}) + \varepsilon_{it} \tag{3}$$

where $\ln w_{it}$ is the log of hourly earnings, s_i is years of schooling and $pexp_{it}$ is the potential experience, defined as "age - schooling - six" which do not distinguish working and non-working periods and $g(.)$ is as cubic function.[16] The primarily interest of the paper is estimating the parameter α_2 which identifies how the returns to potential experience change with schooling. It is important to note that in previous work (table 1) this parameter has been consistently estimated as non-positive; I aim to test whether the same result is found in the sample used in this paper.

The second model estimated is analogous to the typical Mincerian wage model, but I use actual experience instead of potential experience variable:

[16] Mincer (1974) uses log of annual wages and $g(.)$ function is defined as a quadratic function. But since the seminal paper from Murphy and Welch (1990), the convention is to use log of hourly earnings and define $g(.)$ a cubic (or even quartic) polynomial.

$$\ln w_{it} = \gamma_0 + \gamma_1 s_i + \gamma_2 (s_i \times exper_{it}) + k(exper_{it}) + \epsilon_{it} \quad (4)$$

where $exper_{it}$ is the work experience variable, defined as working weeks since an individual left school. The function $k(.)$ is also defined as a cubic function. The coefficient of interest is γ_2 which identifies how returns to actual experience change with schooling.

Finally, I also estimate a wage model that fully characterizes the past employment and unemployment history of workers, as suggested in (Albrecht et al., 1999):

$$\ln w_{it} = \beta_0 + \beta_1 s_i + \beta_2 (s_i \times exper_{it}) + \beta_3 (s_i \times interr_{it}) + f(exper_{it}) + h(interr_{it}) + u_{it} \quad (5)$$

where $exper_{it}$ is work experience and $interr_{it}$ is a measure of career interruptions since leaving school. The objects of interest are the parameters β_2 and β_3, which identify how the returns to work experience and past non-working periods respectively change with schooling.

When modeling an earnings function that accounts for the work history of individuals, a researcher is confronted with some non-trivial choices. First, there is a question regarding the appropriate way to measure career interruptions. It has been shown that different labor force status of individuals during career interruptions might have different impact on subsequent wages (Mincer and Ofek, 1982 and Albrecht et al., 1999). For this reason, I will follow the literature and make the distinction between periods of unemployment, time spent out of the labor force, and military service periods.

Second, one can claim that the timing of career interruptions is also important for earnings determination. With respect to this issue, the literature has suggested different specifications, ranging from the simple accumulation of out-of-work periods since leaving school (Albrecht et al., 1999) to a less parsimonious model, which characterizes the number of weeks out of employment for every year since leaving school (Light and Ureta, 1995). For the main results of the paper I will follow Albrecht et al. (1999) and accumulate periods of unemployment and out-of-work since leaving school. However, in subsection 3.2.3 the analogous results using a less parsimonious model are also presented, where timing of non-working periods is important for earnings.

The final non-trivial choice is how to define the functions $f(.)$ and $h(.)$. In order to be consistent with the most recent literature on the earnings equation (Murphy and Welch (1990)), I define $f(.)$ as a cubic polynomial in the main tables of the paper. By analogy, I will also define $h(.)$ as cubic polynomial, although the coefficients of higher order terms are usually not significant. Nevertheless, I will also present a less-restricted model, where I estimate both $f(.)$ and $h(.)$ non-parametrically in subsection 3.2.2 and the results are qualitatively similar to the ones presented with the cubic assumption.

3.2.1 Main Results

Throughout the paper I normalize the interactions between schooling and measures of work history variables such that coefficient of interactions represent a change in the wage coefficient on schooling with 10 years of experience, unemployment, or OLF periods. All the standard errors presented are White/Huber standard errors clustered at the individual level.

First I investigate whether returns to potential experience do vary with schooling in column (1) of table 4. This column shows the estimation of the traditional earnings model as presented in equation (3). I estimate that the effect of an extra year of schooling on earnings in the beginning of a worker career is 11% (0.006). Most importantly, I find that interaction between schooling and potential experience is not statistically significant. This result is in accordance with Mincer (1974), who found no effects of the interactions between schooling and potential experience on earnings (parallel or convergence of log earnings potential experience profiles across educational groups).

Next, I investigate if the returns to work experience vary with education. In Column (2) I report the estimation of equation (4), which uses working years in the labor market as a measure of actual experience. As can be seen, the result from this specification is remarkably different from the ones using the traditional model. I estimate that the effect of an extra year of schooling on earnings in the beginning of a worker career is 9% (0.004) and that the interaction between schooling and experience is positive. The interpretation is that as returns to experience increases with schooling.

In order to provide further evidence that the returns to actual experience increases with schooling level, I present in table 5 the returns to actual experience for each education group separately. In order to deal with the non-linearity returns to work experience, I defined actual experience in categorical dummies rather than a cubic polynomial. The overall finding is that returns to years of experience is higher for workers with some college and bachelor degree or more than for workers with less than high school or with a high school degree.

Table 6 provides the estimation of the career interruptions earnings model as presented in equation (5). In column (1), as in the past equations, I find a positive and significant coefficient of 0.018 for the interaction between schooling and work experience. Furthermore, I estimate a negative effect of the interaction between past unemployment and schooling. Specifically, I estimate that the wage coefficient on schooling decreases by 2.1%, following *one* year of unemployment. Finally, I find a positive – but not significant – interaction between OLF periods and schooling.[17] But, as discussed in section 3.1, the interpretation for the impact of OLF periods on wage for this demographic group is challenging due to heterogeneous reasons that lead to this type of career interruption.

Columns (2) and (3) provide more robustness to the previous results. In column (2) tenure and its interaction with schooling are added to the model. The idea behind this addition is to investigate whether the main findings of the paper are due to the period a worker is attached to a particular employer, rather than general labor market experience. From these estimations, I find that: i) the coefficients of the career interruptions model are barely affected by the inclusion of these variables; and ii) the wage coefficient on schooling is not significantly affected by tenure. This result suggests that firm-specific mechanisms are not the main explanation for the empirical findings of the paper.

In column (3) Armed Forces Qualification Test score (AFQT) and its interaction with work experience are added to the earnings equation.[18] The AFQT score has been used in the employer learning literature (Farber and Gibbons, 1996 and Altonji and Pierret, 2001) as a measure of a

[17] I also reject with 99% confidence that the coefficient of the interaction between schooling and unemployment is equal to the coefficient of the interaction between OLF periods and schooling.

[18] AFQT is standardized by the age of the individual at the time of the test.

worker's ability that is not easily observed by firms. According to this literature, when AFQT is included with its interaction with experience in the earnings equation, it causes the decreasing with experience (as described in table 1). Note that this result is not found in a model that accounts for career interruptions of workers: while there is a decline of β_2 from columns (2) to (4), the coefficient is still positive and significant. In addition, the other coefficients of interest remain practically unchanged with the inclusion of AFQT in the equation.

As discussed in section 3.1, the main group of interest for this work is non-black males. Nevertheless, one might be interested on the empirical results for other demographic groups. In table 7, I present the results of the career interruption model for black males, non-black females and black females in columns (1), (2) and (3) respectively. The main findings are similar to those for non-black males. For black males and non-black females, I estimate: i) a positive and significant effect of the interaction between work experience and schooling; and ii) a negative effect of the interaction between past unemployment and schooling on earnings. Neither work experience nor cumulative unemployment has a significant effect on the returns to schooling for black females. Finally, past OLF periods have a negative impact on the returns to schooling for both non-black and black females. However, it is well-known that reasons for non-participation periods are substantially different for males and females, which poses a challenge for comparing the results for these two groups.

Finally, table 8 provides robustness check that the main results of the paper are not sensitive to the definition of the year of leaving school. In precise terms, and different from the other results of the paper, in this table a worker enters the labor market when he first leaves school and the accumulation of work, unemployed and OLF weeks start in this period. As discussed before, on one hand, some of the career interruptions can be justified by a decision of a worker to return to school after spending some time in the labor market. On the other hand, I can account for employment periods a worker had before returning to school in the construction of the work experience.

The table shows that the results using this definition for year of leaving school is very similar to the ones presented in table 6. In fact, in column (1) I estimate a 7% effect of schooling on earnings at the beginning of a workers career. Second, there is a positive and significant coefficient of interaction between schooling and work experience of 0.018. In contrast, there is a negative effect of the interaction between past unemployment and schooling of 0.151 and insignificant effect of OLF periods on the returns to schooling. In addition, in columns (2) and (3) I find similar results when including tenure and AFQT and its interactions with schooling and work experience respectively on the wage equation.

3.2.2 Earnings Profiles and Nonparametric Regressions

In this subsection I estimate a less restricted earnings model without imposing functional form assumptions on the relation between work experience, cumulative unemployment, and OLF years and earnings. In these estimations I also substitute years of schooling with educational degree dummies. This procedure allows the model to account for non-linearity in the relation between schooling and earnings. The earnings profiles are plotted with respect to work experience, cumulative years unemployed, and cumulative years OLF for different educational groups. The estimated non-parametric model is the following:

$$\ln w_{it} = f_s(exper_{it}) + h_s(cunemp_{it}) + g_s(colf_{it}) + \eta_{it} \tag{6}$$

where s represents educational group variables: less than high school, high school degree, some college and bachelor degree or more. As before $exper_{it}$ is work experience. I also define $cunemp_{it}$ as the cumulative years a work spent unemployed, and $colf_{it}$ as the cumulative years a worker spent OLF. Different from model (5), there is no imposition of any parametric restriction on $f_s(.)$, $h_s(.)$ and $g_s(.)$. However, I still impose the additive separability of the work history variables in the model. The method used for the non-parametric estimation is the differentiating procedure described in Yatchew (1998).[19] I use locally weighted regressions using a standard tricube weighting

[19] In this method, I estimate each function $f_s(.)$, $h_s(.)$, $g_s(.)$ separately, imposing a functional form assumption for the non-estimated functions. In precise terms, when estimating $\hat{g}_s(.)$, I assume that $f_s(.)$ and $h_s(.)$ are cubic polynomial but impose no parametric restriction on $g_s(.)$. The same procedure is applied when estimating $\hat{f}_s(.)$ and $\hat{h}_s(.)$.

function and a bandwidth of 0.5 when estimating f_s and 0.25 when estimating h_s and g_s.[20]

Figure 3 plots the estimate of $f_s(.)$ for different educational groups. The figure shows that the log earnings-work experience profiles have a concave shape as previously found in the literature (Murphy and Welch, 1992), with wages growing faster at the beginning of a worker's career. In contrast to previous literature, I estimate a much steeper wage growth for more educated workers, than for uneducated workers. In fact, the figure shows that the wage gap between individuals with at least a college degree and other workers tends to increase as workers accumulate actual experience. Similarly, the wage gap between high school graduates and workers with less than a high school education is smaller than it is for workers with zero work experience, but increases significantly as workers accumulate experience. These results are in accordance with the findings presented in table 4, namely that the wage coefficient on earnings increases, as workers accumulate actual experience throughout their careers.

Figure 4 presents the non-parametric estimation of the relation between log earnings and cumulative years of unemployment, defined by the function $h_s(.)$ in equation (6), for different educational groups. The figure shows that both college and high school graduates are negatively affected by unemployment periods, as wages decline with the accumulation of this variable. However, the rate of wage decline is substantively different across educational groups since workers with a bachelor's degree have a greater wage decline with unemployment. It is also notable that the wages of workers with less than a high school degree are not significantly affected by unemployment.

Finally, figure 5 plots the analogous estimation of the relation between log earnings and cumulative years that a worker spends out of the labor force, as described by the function $g_s(.)$. The evidence shows that this relation is quite heterogeneous among the groups. While the earnings of workers with at least a college degree are almost not affected at all by the accumulation of OLF, workers with less than a high school degree face a substantial wage decrease with OLF periods. The interpretation of these results is difficult because non-participation periods have heterogeneous justifications among workers.

[20] The overall results of this graph are not sensitive to the choice of different bandwidths.

3.2.3 Timing of Career Interruptions

This section addresses whether accounting for timing of career interruptions in the earnings equation can affect the main findings of the paper. For this reason, instead of assuming that wages are affected by the cumulative unemployment and out-of-the-labor-force periods, I estimate the following log wage model separately by educational groups:

$$\ln w_{it} = \beta_0^S + \beta_1^S + f_s(exper_{it}) + \sum_{j=1}^{5} \gamma_j^s unemp_{it-j} + \sum_{j=1}^{5} \alpha_j^s olf_{it-j} + \eta_{it} \tag{7}$$

where s represents educational group variables: less than high school, high school degree, some college, and bachelor degree or more; $unemp_{it-j}$ is the number of weeks a worker spent unemployed in the calendar year that was j years before the interview and olf_{it-j} is the number of weeks a worker spent out of the labor force in the calendar year that was j years before the interview date. For example, for t =1993, the variable $unemp_{it-3}$ reports the number of weeks a worker spent unemployed in 1990 and olf_{it-3} the number of weeks a worker spent OLF in 1990.[21] I divide $unemp_{it-j}$ and olf_{it-j} by 52, allowing the coefficients to be interpreted as changes of year units. Finally, I limit the sample to observations of a worker 5 years after leaving school, so past work history variables reflect events that happened after a worker made the transition to the labor market.

Figure 9 plots the estimation of the coefficients γ_j^s with a 95% confidence interval for different s and j. The graph shows a few interesting facts. First, the weeks spent unemployed in the past calendar year have the highest impact on earnings for all education groups, but the effects are much higher for workers with a bachelor's degree or higher. In precise terms, the estimation shows that spending the previous calendar year unemployed decreased the earnings of this group by 60%. Second, unemployment periods have a long-term impact on earnings, with a significant negative effect of unemployment weeks, which occurred 5 years prior to the interview. While the difference across educational groups is not as strong, this figure shows that educated workers are also more

[21] These career interruption variables are constructed based on the week-by-week work history information provided by NLSY, which identifies with precision the periods of unemployment and OLF throughout a worker's career.

affected by older unemployment periods.

In figure 7, the analogous statistics for α_j^s are reported with a 95% confidence interval, showing that periods spent out of the labor force have a negative impact on the earnings of all workers. However, this effect is much lower than those estimated by unemployment periods, and tend to disappear with time. Finally, while it is estimated that college-graduate workers are more affected by past year OLF weeks than educated workers, the differences across educational groups are not as strong for OLF periods as they are for unemployment periods.

Figures 6 and 7 bring to light how unemployment and OLF periods affect the effect of schooling on earnings. In order to provide a more accurate test regarding whether the returns to schooling change throughout a workers' career – in a model where timing of career interruptions affect wages – I estimate the model below:

$$\ln w_{it} = \beta_0 + \beta_1 s_i + \beta_2 (s_i \times exper_{it}) + f(exper_{it}) + \sum_{j=1}^{5} \lambda_j unemp_{it-j} \tag{8}$$

$$+ \textstyle\sum_{j=1}^{5} \pi_j (s_i \times unemp_{it-j}) + \sum_{j=1}^{5} \rho_j olf_{it-j} + \sum_{j=1}^{5} \psi_j (s_i \times olf_{it-j}) + \epsilon_{it}$$

where all the variables have the same definitions as before and s_i is a measure of years of schooling. In this framework, the coefficients of interest are β_2, which identifies how the wage coefficient on schooling changes with work experience, π_j which identifies how the wage coefficient on schooling changes with past unemployment periods j years before the interview and ψ_j which identifies how the wage coefficient on schooling changes with past OLF periods j years before the interview.

The result of the estimation of the earnings model 8 is presented in table 9. While I estimate the model including olf_{it-j} and its interaction with s_i , for the sake of space these coefficients are omitted in the table. The result shows that ψ_j is not significant for any j. As can be seen in the table: first, the wage coefficient on schooling increases with work experience, even in a model where the timing of career interruption matters, as presented in columns (1) - (3). As can be seen, the estimated β_2 is not very different from the one estimated in table 4. Second, as column (2) shows, previous unemployment periods have a significant negative impact on earnings, with previous year unemployment having the highest impact. Third, column (3) shows that, although there is an estimated negative effect of all unemployment periods on the wage coefficient on schooling for all years, recent unemployment periods have a higher impact on earnings. The overall interpretation of these findings is that, while timing of unemployment and OLF might matter for earnings determination, this less-restricted model shows similar patterns, in terms of the effect of work experience and career interruptions on the wage coefficient on schooling, as the one presented in subsection 3.2.1.

3.2.4 Individual Fixed-Effects Estimates

An issue that emerged in models that fully characterize an individual's work history is the possible endogeneity problem of actual experience and career interruptions. The main argument is an omitted variable problem. It is possible that there are some variables not observed in the data that are related to both current wage determination and past employment. For example, workers with higher career aspirations might have higher employment attachment throughout their life-cycle earnings. In both cases, the seriousness of the endogeneity problem depends on how strong the correlation between current and past levels of the earnings residuals is, and whether past residuals are related to the employment attachment of workers.

A popular approach in the literature when dealing with possible endogeneity of work history is based on an individual fixed effect assumption (Corcoran and Duncan, 1979, Kim and Polachek, 1994, Light and Ureta, 1995 and Albrecht et al., 1999).[22] The basic idea of this approach is that the factor related to past employment attachment of workers, which causes the correlation of earnings residuals across time, is an individual-specific fixed component. In terms of the model presented in equation 5, the fixed effect assumption means that u_{it} can be written as a sum of an individual

[22] There are other suggestions in the literature with respect to ways of addressing the possible endogeneity of work history. Mincer and Polachek (1974) suggest using family characteristics, such as education of the partner or number of children, as instruments for previous working and non-working periods of married women. While it is questionable as to how exogenous these variables truly are, there is evidence that family characteristics have a weak relation to employment attachment of non-black males, the main group of interest of this work. Alternatively, Altonji and Pierret (2001) suggest using potential experience ($pexp_{it}$) as an instrument for actual experience, in a model that earnings are not affected by unemployment periods. However, if career interruptions have impact on wages, the potential experience variable is not a validity instrument for actual experience. In this circumstance, $pexp_{it}$ is not redundant (or ignorable) in the log wage expectation, such that: $\mathbb{E}[\ln w_{it}|exper_{it}] \neq \mathbb{E}[\ln w_{it}|exper_{it}, pexp_{it}] = \mathbb{E}[\ln w_{it}|exper_{it}, interr_{it}]$.

component ϕ_i and a transitory component η_{it}, both with mean zero and constant variance. While η_{it} is independent of an individual's work history, the work history variables can be correlated to ϕ_i.

Table 10 presents the main results of the estimation of the wage model described by equation (5) using an individual fixed effect estimation. Note that as schooling does not change overtime, I cannot identify β_1 when using this estimation strategy. However, it is possible to identify the effect of its interaction with other time-varying variables, such as work experience, tenure, and cumulative years OLF and unemployment. In order to make these new results comparable to the least square estimation, the same specifications are followed in this table as the one presented by the least square estimation of table 4.

The overall results from table 8 are qualitatively and quantitatively similar to those estimated by the least square estimation of table 4. Namely, the wage coefficient on schooling increases significantly as a worker accumulates work experience, and decreases as a worker accumulates unemployment periods. If anything, the fixed effect estimation shows a lower negative coefficient for the effect of unemployment on the returns to schooling. In other words, this new estimation leaves the conclusions based on the OLS regressions intact.

This result is not surprising in light of the findings of existing literature. Mincer and Polachek (1974), Blackburn and Neumark (1995), and Albrecht et al. (1999) have found that coefficients of the earnings model stay virtually unchanged when dealing with the possible endogeneity problem of work history variables. From these results, one can conclude that the endogeneity of work history appears to be less of a problem when estimating career interruptions models.

4 Model

The dynamics estimated thus far are remarkably different from those in the existing literature. In a departure from the past empirical literature, my research finds that more educated workers receive a higher earnings increase with actual experience, while suffering greater earnings losses after unemployment periods. The natural question is if it is possible to conciliate these novel empirical findings with the existing theories for earnings dynamics. In this section, I present a simple two period model that can explain the empirical findings of this paper. The model is based on theories of on-the-job training and layoffs decisions under asymmetric information, as presented in Acemoglu and Pischke (1998) and Gibbons and Katz (1991) respectively. I extend these types of model by allowing firms to use information on worker's schooling to predict unobservable ability when making training decisions in the first period.

4.1 The model environment

The world has two periods and firms can hire workers at the beginning of either period. All firms and workers are risk-neutral and there is no discounting between periods. In period one, the output produced by a worker is defined as $y_1 = g(s)$ where s is the schooling level $s = \{1, ...S\}$ and $g(s) \geqslant g(s')$ for any $s > s'$. The production on the second period depends on training level τ provided by the current employer. There are quadratic costs associated with training $C(\tau) = \tau^2/2$, which ensure that some training is optimal for some workers.

If a worker remains with the first period employer, in the second period he produces:

$$y_2 = \tau\eta + g(s) \tag{9}$$

where η is the worker's ability to learn on the job. An important assumption is that ability and training are complementary, what is captured by the multiplicative specification of η and τ .[23]

Not all human capital is general and if a worker switches employers, he or she can only bring a share $1 - \delta$ of his training. As a consequence, a worker produces

$$y_2 = (1 - \delta)\tau\eta + g(s)$$

if he switches employers in the second period. An interpretation is that a share δ of training is devoted to building firm specific human capital and a share $1 - \delta$ is devoted to building general human capital. I assume that employers cannot distinguish which type of training they provide to

[23] The complementary between ability and training is also present in Acemoglu and Pischke (1998)

their workers. This assumption allows firms to invest in general job training as increasing general human capital raises productivity more than outside wages. [24]

A worker's ability is unknown to all agents at the beginning of the first period but employers have access to a worker's schooling information s. Ability takes only two values: $\eta = 1$ with probability p_s and $\eta = 0$ with probability $1 - p_s$, with $p_s$being the proportion of workers with schooling s that are high ability. Educated workers are more likely to be high ability and $p_s > p_{s-1}$ for any s.

The sequence of events is as follows:

- In the first period, a worker is hired and the employer decides how much training τ to provide as well as a wage level w_1. At this stage training and wage decisions are only based on worker's education.

- At the end of the first period, current employer observes the worker's first-period output and so perfectly infers the worker's ability, but prospective employers do not observe output. After observing a worker's ability, the current employer makes lay-off decisions. We define $L = L(\eta, s)$ as the decision of the firm to lay-off worker with ability η and schooling s.

- Following a layoff, prospective employers observe workers that were laid off, their training level and their education level. Based on this information, prospective employers make wage offers to both retained and laid-off workers. Competition among prospective employers guarantees that their wage offer equals the expected productivity given the available information at the moment:

$$v_2(s, \tau, L) = \mathbb{E}[(1 - \delta)\tau\eta + g(s)|\tau, s, L] \tag{10}$$

- The current employer observes the offers from prospective employers and then makes its second-period wage offer to retained workers. We define as w_2 as the wage offered to workers by current employer.

[24] This assumption is analogous to the Acemoglu and Pischke (1999) assumption that if firm-specific skills and general skills are complements in the production function.

- Finally, the worker chooses the highest of the wages offered, preferring to stay with the current employer in case of a tie.

4.2 Separating Equilibrium

Equilibrium is characterized by a function of the a worker's schooling s and ability level η to wage level in the first period w_1^*, a training level τ^*, a layoff decision L^*, an offer from prospective employers v_2^*, a wage offer from current employer to retained workers w_2^* and a worker's decision on staying with the current employer or switch jobs. As in Acemoglu and Pischke (1998), depending on the parameter values, the model can lead to multiple equilibria.

We restrict the analysis to a separating equilibrium where for any education level, the current employer lays-off its low ability workers and retain high ability workers. In this equilibrium, the lay-off decision perfectly reveals to prospective employer a worker's unobserved ability. This extreme case highlights the mechanisms of adverse selection I want to stress with the model and simplifies the derivations of the predictions of the model. I assume that firms follow this layoff decision rule and prospective firms believe that the current employer follows this action. Then I show that the current firm has no incentives to deviate from this strategy.

If prospective employers believe that the current firm lays off a worker if and only if the worker is low ability, the then the reemployment wage of a laid-off worker will be:

$$v_2^*(s, \tau, L = 1) = g(s) \tag{11}$$

and wage offer to retained worker will be:

$$v_2^*(s, \tau, L = 0) = (1 - \delta)\tau^* + g(s)$$

Given these outside offers, the current employer's best response is to try to retain the worker by offering the market wage. Incumbent firms must pay their workers at least what they can earn if they switch employers:

$$w_2^* = (1-\delta)\tau^* + g(s) \tag{12}$$

Note that this wage is strictly below a worker's actual productivity. This result is due to the firm specific component associated with training which creates a rent for the current employer. If a worker changes jobs, his productivity declines because he loses his firm-specific human capital. In fact, the second period profit $\delta\tau^*$ is a function of firm-specific component of the job-training, and indirectly a function of a worker's schooling level.

Given the prospective employers believes and optimal wage offers, it is easy to show that current employer has no incentives to deviate from its lay-off strategy. Firms make profit from high ability workers with all schooling levels and therefore the firm has incentives to keep any high ability worker. In the same way, if the firm keeps a low ability worker, the market bids up his or her wage offer and the firm will find it unprofitable to retain such worker. As prospective employers only hire laid-off workers in this equilibrium, I will refer to v_2^* as the wage of laid-off workers in period 2.

Now we turn to optimal decisions of the firm in period one. In the first period, employer do not know a worker's true ability and make training decisions based on schooling information in order to maximize expected profits:

$$\max_\tau p_s(\tau + g(s) - w_2^*) - \tau^2/2 - w_1 + g(s)$$

Given the equilibrium wage in the second period (12), and making use of first order condition, we can write the optimal training level of the firm that maximizes profits

$$\tau^* = p_s\delta \tag{13}$$

which is positively related to schooling level as well as the firm-specific component of the job-training. The interpretation is that firms have a higher expectation that more educated workers are high ability and therefore more likely to be retained in the second period. The relation between training and δ is justified because the monopsony power of current firm is positively related to the firm specific component of on the job training.

Finally, we impose a free entry condition on firms at all points in time which implies that in equilibrium no firm will earn positive profits. This condition will determine wages in the first period during this period. Based on equilibrium wages in the second period, we can express wages in the first period as:

$$w_1^* = g(s) + p_s\delta\tau^* - \frac{{\tau^*}^2}{2} \tag{14}$$

The term $g(s)$ represents the productivity of a worker in the first period and the component $p_s\delta\tau^* - \frac{{\tau^*}^2}{2}$ represents the expected profit of worker given the information available in the first period. Using the optimal training level from (13), we can rewrite the expected profits in the second period as $(p_s\delta)^2/2$, which is increasing with schooling and the firm specific component of job training δ.

4.2.1 Wage Predictions

To conclude this section, I describe some properties of wages in this separating equilibrium. In order to match definitions of the empirical section of the paper, I refer to w_1^* as the wage of workers with no work experience, w_2^* as the wage of worker with one period of work experience and no unemployment spells, and v_2^* as the wage of a worker with one period of work experience and one unemployment spell.

Proposition 1: w_1^* and w_2^* are strictly increasing with schooling and v_2^* is non-decreasing with schooling.

The proof follows the equilibrium wages derived in equations (10), (12), and (14). In all states, the equilibrium wage has a productivity component $g(s)$ which is non-decreasing with s. In addition, the wage of worker in period one w_1^* has an expected profit component $(p_s\delta)^2/2$, which is strictly increasing with schooling. The intuition is that educated workers are expected to be more profitable as they have a higher return to on-the-job training. As a consequence of the zero profit condition, wages in the first period are strictly increasing with education. In the second period, wages of retained workers w_2^* is defined by a worker's productivity at prospective employers, which is determined by the general on-the-job training $(1-\delta)\tau^*$. As more educated workers receive higher training, wages of retained workers are strictly increasing with education as well.

Proposition 2: Wages increase with work experience if firms' monopsony power is sufficiently small.

The proof of this proposition follows from equations (12) and (14). The effect of work experience on wages is given by the wage increase for workers that are retained by the firm in period two:

$$w_2^* - w_1^* = (1-\delta)\tau^* - \frac{{\tau^*}^2}{2}$$

Based on this equation, it is easy to show that wage increases with experience if $\tau^* < 2(1-\delta)$ for any level of education. Using the optimal training level from (13) one can demonstrate that this condition is satisfied if $p_S < \frac{2(1-\delta)}{\delta}$, where S is the highest schooling level that a worker can achieve.

The term δ represents the firm specific component of the job training, which creates a rent for the firm as it allows the current employer to pay workers a wage lower than their productivity in the second period. This term can be defined as the firms' monopsony power over workers. A greater δ affects wages in two different ways: i) wages in first period are high because expected profits are high; ii) wages for retained workers are low because the general component of on-the-job training is low. As a consequence, even if workers receive job-training, wages only increase with experience if firms can only extract low rents from workers.

Proposition 3: Educated workers have a higher wage increase with experience if firms' monopsony power is sufficiently small.

The proof of this proposition is very similar to the proof of proposition 2. Using the equilibrium training level from (13), I can write the wage change with experience as a function of p_s:

$$w_2^* - w_1^* = (1-\delta)p_s\delta - \frac{(p_s\delta)^2}{2}$$

If the monopsony term δ is such that $p_S < \frac{(1-\delta)}{\delta}$, the difference $w_2^* - w_1^*$ is increasing with p_s and therefore with schooling.

The intuition for this result is straightforward. In period 1, firms believe that educated workers are more likely to be high ability. As a consequence i) the expected profits of educated worker are high and therefore first period wages are high; ii) educated workers receive higher training and therefore are more productivity in period two. If the current employer can extract most of the rents from job-training, then educated workers might not benefit from their higher job-training. However, if δ is small, educated workers receive higher return from the human capital investment and have a higher wage increase with experience compared to less educated workers.

Proposition 4: Laid off workers receive lower wages than retained workers.

The effect of beginning laid off on earnings is given by the wage difference between workers with one period of work experience and one unemployment spell and workers with one period of experience and zero unemployment spells:

$$v_2^* - w_2^* = -(1-\delta)\tau^*$$

which is negative at any training level. The interpretation of this result is same as Gibbons and Katz (1991): when employers have discretion with respect to whom to lay off, the market infers that laid-off workers are of low ability and therefore offers them low wages in their next jobs. Note that in this model only high ability workers can benefit from training. As a consequence, workers with higher training level suffer greater wage losses when they are laid-off.

Proposition 5: Educated workers suffer higher wage loss when they are laid off.

As demonstrated before, the effect of beginning laid off on earnings is given by $-(1-\delta)\tau^*$. As the training level τ^* is positively associated with schooling, more educated workers suffer a greater wage loss when they are laid-off. The intuition is that firms make greater training investments on educated workers in period one. However, only high ability workers can benefit from training in the second period and the training investment is wasted for those workers that are laid-off. An interpretation of this result is that employers are more surprised by the revelation that a educated worker is low ability and therefore educated workers suffer a higher wage loss after being laid-off.

5 Conclusion

The potential experience variable might generate greater downward bias for workers with high employment attachment throughout their careers if these workers suffer greater wage losses after unemployment periods. For this reason, this paper emphasizes the importance of distinguishing the returns to actual experience from the returns to potential experience. Indeed, I show that a known feature of the Mincerian wage equation does not hold when using accurate measures of work experience. While consistent with past work, I find that returns to potential experience do not vary with education, I estimate that more educated workers have a higher wage increase with actual experience. This potential experience bias associated to wage drops after career interruptions is not discussed in the literature. I hope this article may facilitate future research on how the returns to experience vary across gender, race, immigration status, as this source of bias might also be present in such estimations.

Given the novelty of these empirical findings, I proposed a model that can rationalize the results of this paper. The model is an extension of traditional on-the-job training with asymmetric information models, but allowing firms to use a worker's education to predict his or her unobservable ability. In the model, educated workers receive more on-the-job training in the first period because they are more likely to be high ability. However, more educated workers also suffer a higher wage loss after being laid-off because employers are more surprised to learn that an educated worker is low ability. While the proposed model can predict the empirical findings of the paper, by no means this is the only possible framework where such predictions can be generated. For example, on-the-job searching models where quality of search is related to education could explain higher wage growth with experience for more educated workers. In addition, the human capital depreciation associated with unemployment periods could predict a higher wage loss after unemployment for more educated workers. I hope the link between different models and other empirical predictions can be derived in the future to determine which are the mechanisms driving a higher wage increase with experience and greater wage losses after unemployment for more educated workers.

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Table 1 - Literature Review

Study	Data	Dependent Variable	Experience Specification	Sample	Main Findings
Mincer (1974)	U.S. Census, 1960	Log Annual Earnings[25]	Age-Schooling-6	White, non-farm, non student men up to age 65.	"Experience profiles of log earnings are much more nearly parallel."
Faber and Gibbons (1996)	NLSY 1979-1991	Hourly Wage (level)	Time since long-term transition to the labor force	Males and females after long-term transition to the labor force.	"The estimated effect of schooling on the level of wages is independent of labor-market experience."
Altonji and Pierret (2001)	NLSY 1979-1992	Log Hourly Wage	Age-Schooling-6[26]	White or black males with eight or more years of education.	"Wage coefficients on the variables that firms cannot observe and affect workers' productivity rise with experience while the coefficient on education falls."
Lemieux (2006)	CPS 1979–1981, 1989–1991, and 1999–2001	Log Hourly Wage	Age-Schooling-6	Men age 16 to 64 with 0 to 40 years of potential experience.	For 1979-1981 the experience profiles are parallel; For 1989-1991 and 1999-2001 the college-high school wage gap declines as a function of experience.
Heckman et al. (2006)	U.S. Census, 1940-1990	Log Annual Earnings	Age-Schooling-6	White and black males.	"The estimated profiles for white males from the 1940–1970 Censuses generally support the parallelism by experience patterns. Log earnings–experience profiles for the 1980–1990 Censuses show convergence for both white and black males."

[25] Mincer only finds insignificant effects of the interaction between schooling and experience when controlling for weeks worked in the past year.
[26] In Panel 2 of Table 1, the authors present their results using actual experience instrumented by potential experience. I discuss the validity of this approach in section 3.2.4.

Table 2 - Work History Variables

Variable	**Definition**
Potential Experience	Age - Schooling - 6
Time since leaving school	Weeks since leaving school /52
Work Experience	Weeks worked since leaving school /52
Cumulative Years OLF	Weeks OLF since leaving school /52
Cumulative Years Unemployed	Weeks Unemployed since leaving school /52
Cumulative Years in Military Services	Weeks in the Military Services since leaving school /52

Table 3 - Descriptive Statistics

Variable	Education Level			
	Less than High School	High School Degree	Some College	BA or More
Log Hourly Wage (1999 dollars)	2.00	2.25	2.44	2.80
Potential Experience	16.07	14.48	14.91	13.24
Time since graduation	14.21	14.14	12.46	11.52
Work Experience	11.04	11.87	10.86	10.68
Cumulative Years OLF	1.58	1.03	0.82	0.43
Cumulative Years Unemployed	1.41	0.76	0.40	0.24
Cumulative Years in Military Services	0.01	0.36	0.27	0.10
Cumulative Years Unaccounted	0.17	0.12	0.10	0.07
Individuals	224	1,083	508	669
Observations	3,432	16,750	6,138	7,387

Note: See Table 2 for definitions of the work history variables.

Table 4 - Schooling, Potential Experience, Actual Experience and Earnings

NLSY 1979 - Non-Black Males

Dependent Variable: Log Real Hourly Wage

Method: Least Squares

Model	(1)	(2)
Schooling	0.111	0.0967
	(0.006)***	(0.0041)***
Potential Experience	0.095	
	(0.009)***	
Potential Experience^2	-0.004	
	(0.0004)***	
Potential Experience^3	0.0001	
	(0.0000)***	
Schooling * Potential Experience/10	0.004	
	(0.004)	
Work Experience		0.074
		(0.007)***
Work Experience^2		-0.004
		(0.0003)***
Work Experience^3		0.0001
		(0.0000)***
Schooling * Work Experience/10		0.016
		(0.003)***
Observations	33,707	33,707
R-squared	0.260	0.293

*** p<0.01, ** p<0.05, * p<0.1, Control: Year dummies

White/Huber standard errors clustered at the individual level are reported in parentheses.

Table 5 - Schooling, Experience Dummies and Earnings

NLSY 1979 - Non-Black Males

Dependent Variable: Log Real Hourly Wage

Method: Least Squares

Sample	Less than High School	High School or Equivalent	Some College	Bachelor or More
Work Experience Dummies:				
1< Work Experience <=2	0.100	0.069	0.240	0.318
	(0.049)**	(0.035)**	(0.065)***	(0.084)***
2< Work Experience <=3	0.117	0.176	0.388	0.353
	(0.047)**	(0.034)***	(0.069)***	(0.084)***
3< Work Experience <=4	0.184	0.263	0.441	0.421
	(0.053)***	(0.034)***	(0.068)***	(0.083)***
4< Work Experience <=5	0.255	0.338	0.508	0.440
	(0.054)***	(0.036)***	(0.070)***	(0.086)***
5< Work Experience <=6	0.289	0.390	0.552	0.482
	(0.056)***	(0.037)***	(0.072)***	(0.086)***
6< Work Experience <=7	0.329	0.433	0.590	0.532
	(0.058)***	(0.038)***	(0.071)***	(0.088)***
7< Work Experience <=8	0.392	0.460	0.596	0.528
	(0.063)***	(0.039)***	(0.074)***	(0.089)***
8< Work Experience <=9	0.398	0.520	0.603	0.564
	(0.066)***	(0.041)***	(0.077)***	(0.090)***
9< Work Experience <=10	0.462	0.545	0.676	0.584
	(0.070)***	(0.042)***	(0.077)***	(0.091)***
10< Work Experience <=11	0.533	0.573	0.620	0.624
	(0.066)***	(0.044)***	(0.081)***	(0.094)***
11< Work Experience <=12	0.500	0.620	0.715	0.651
	(0.075)***	(0.045)***	(0.080)***	(0.095)***
12< Work Experience <=13	0.555	0.641	0.745	0.644
	(0.077)***	(0.047)***	(0.081)***	(0.097)***
13< Work Experience <=14	0.490	0.640	0.734	0.631
	(0.083)***	(0.048)***	(0.083)***	(0.098)***
14< Work Experience <=15	0.535	0.693	0.799	0.680
	(0.087)***	(0.050)***	(0.087)***	(0.098)***
Work Experience > =15	0.663	0.813	0.801	0.668
	(0.087)***	(0.055)***	(0.090)***	(0.103)***
Observations	3,432	16,750	6,138	7,387
R-squared	0.094	0.131	0.126	0.167

Omitted Work Experience Less than 1

*** p<0.01, ** p<0.05, * p<0.1, Control: Year dummies

White/Huber standard errors clustered at the individual level are reported in parentheses.

Table 6 -Schooling, Experience, Career Interruptions and Earnings

NLSY 1979 - Non-Black Males

Dependent Variable: Log Real Hourly Wage

Method: Least Squares

Model	(1)	(2)	(3)
Schooling	0.082	0.083	0.066
	(0.005)***	(0.005)***	(0.006)***
Schooling * Work Experience/10	0.018	0.014	0.014
	(0.003)***	(0.004)***	(0.004)***
Schooling * Cumulative Years Unemployed /10	-0.218	-0.207	-0.245
	(0.038)***	(0.038)***	(0.039)***
Schooling * Cumulative Years OLF /10	0.022	0.022	0.031
	(0.024)	(0.024)	(0.025)
Schooling * Tenure Years/10		0.002	
		(0.006)	
AFQT * Work Experience/10			0.020
			(0.008)**
Observations	33,707	33,181	32,162
R-squared	0.321	0.325	0.338
Tenure	No	Yes	No
AFQT	No	No	Yes
Other controls:	Cubic Polynomial of Work Experience, Cumulative Years OLF/Unemployment/Military; Uncounted Years; and Years Dummies		

*** p<0.01, ** p<0.05, * p<0.1

White/Huber standard errors clustered at the individual level are reported in parentheses.

Note: AFQT is normalized to have a standard deviation of 1. Difference in the number of observations between models (1) , (2) and (3) is due to 526 observations of individuals with missing tenure and 1,545 observations of individuals with missing AFQT information.

Table 7- Schooling, Experience, Career Interruptions and Earnings - Other Demographic Groups

NLSY 1979 - Other Demographic Groups

Dependent Variable: Log Real Hourly Wage

Method: Least Squares

Sample	Black Males	Non-Black Females	Black Females
Schooling	0.106	0.092	0.111
	(0.015)***	(0.005)***	(0.012)***
Schooling * Work Experience/10	0.019	0.011	0.004
	(0.009)**	(0.004)***	(0.008)
Schooling * Cumulative Years Unemployed /10	-0.238	-0.155	-0.077
	(0.071)***	(0.047)***	(0.061)
Schooling * Cumulative Years OLF /10	-0.008	-0.049	-0.066
	(0.053)	(0.007)***	(0.017)***
Observations	4,228	29,543	4,004
R-squared	0.312	0.350	0.342
Controls:	Cubic Polynomial of Work Experience, Accumulated OLF/Unemployment/Military Years; Uncounted Years; and Years Dummies		

*** p<0.01, ** p<0.05, * p<0.1

White/Huber standard errors clustered at the individual level are reported in parentheses.

Table 8 - Schooling, Experience, Career Interruptions and Earnings - Leaving School Year as First Year a Responded Left School

NLSY 1979 - Non-Black Males

Dependent Variable: Log Real Hourly Wage

Method: Least Squares

Model	(1)	(2)	(3)
Schooling	0.070	0.070	0.057
	(0.005)***	(0.005)***	(0.006)***
Schooling * Work Experience/10	0.018	0.013	0.014
	(0.003)***	(0.003)***	(0.003)***
Schooling * Cumulative Years Unemployed /10	-0.151	-0.137	-0.167
	(0.027)***	(0.027)***	(0.028)***
Schooling * Cumulative Years OLF /10	-0.003	-0.000	-0.003
	(0.013)	(0.013)	(0.014)
Schooling * Tenure Years/10		0.009	
		(0.001)***	
AFQT * Work Experience/10			0.024
			(0.008)***
Observations	38,267	37,665	36,571
R-squared	0.311	0.318	0.325
Tenure	No	Yes	No
AFQT	No	No	Yes
Other controls:	Cubic Polynomial of Work Experience, Cumulative Years OLF/Unemployment/Military; Uncounted Years; and Years Dummies		

*** p<0.01, ** p<0.05, * p<0.1

White/Huber standard errors clustered at the individual level are reported in parentheses.

Note: Different from the other results, in this table I define year of leaving school as the first year a responded has left school. See section 3.1 for details. AFQT is normalized to have a standard deviation of 1. Difference in the number of observations between models (1), (2) and (3) is due to 602 observations of individuals with missing tenure and 1,696 observations of individuals with missing AFQT information.

Table 9- Unemployment, Schooling and Earnings by Timing of Unemployment

NLSY 1979 - Non-Black Males, 1983-2010
Dependent Variable: Log Real Hourly Wage
Method: Least Squares

Model	(1)	(2)	(3)
Schooling	0.104	0.080	0.091
	(0.004)***	(0.004)***	(0.005)***
Schooling * Work Experience/10		0.021	0.016
		(0.003)***	(0.004)***
Weeks spent unemployed/52			
Last year	-0.219	-0.229	0.448
	(0.026)***	(0.025)***	(0.142)***
2 years ago	-0.13	-0.14	0.011
	(0.023)***	(0.023)***	-0.133
3 years ago	-0.085	-0.097	0.163
	(0.021)***	(0.021)***	-0.129
4 years ago	-0.101	-0.112	0.121
	(0.021)***	(0.021)***	-0.133
5 years ago	-0.112	-0.124	0.219
	(0.022)***	(0.022)***	(0.128)*
Schooling * Weeks spent unemployed/52			
Last year			-0.056
			(0.012)***
2 years ago			-0.012
			(0.011)
3 years ago			-0.022
			(0.010)**
4 years ago			-0.020
			(0.011)*
5 years ago			-0.029
			(0.011)***
Observations	31,711	31,711	31,711
R-squared	0.303	0.306	0.308

Controls: Cubic Polynomial of Work Experience, Weeks spent OLF in each of the past 5 year (and their interaction with schooling in model 3), Uncounted Years and Years Dummies
*** p<0.01, ** p<0.05, * p<0.1
White/Huber standard errors clustered at the individual level are reported in parentheses.

Note: The sample is restricted to observations 5 years after an individual's leaving school. Weeks spent in each labor status are constructed using annual aggregation of the week-by-week records.

Table 10 - Schooling, Experience, Career Interruptions and Earnings, Individual Fixed Effect

NLSY 1979 - Non-Black Males

Dependent Variable: Log Real Hourly Wage

Method: Fixed Effects

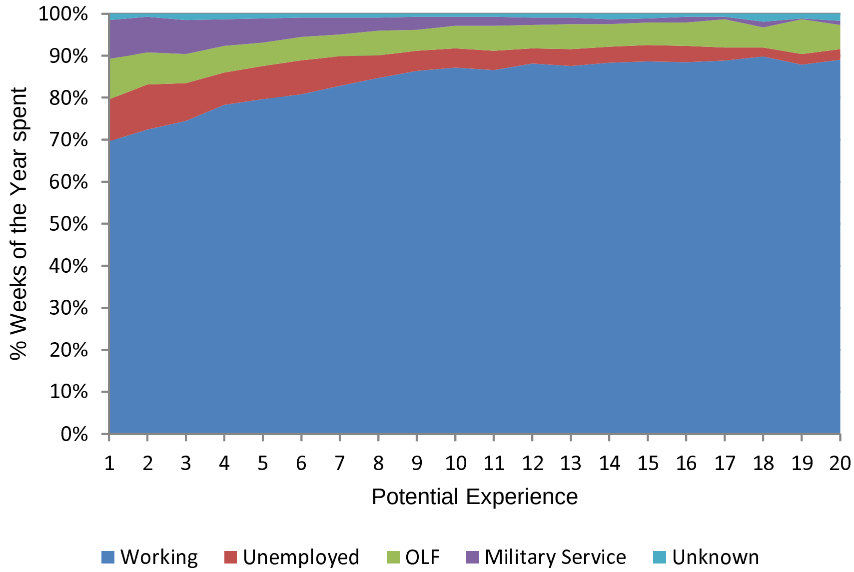
Model	(1)	(2)	(3)
Schooling * Work Experience/10	0.020	0.015	0.013
	(0.003)***	(0.004)***	(0.004)***
Schooling * Accumulated Unemployment Years/10	-0.095	-0.084	-0.114
	(0.036)***	(0.036)**	(0.036)***
Schooling * Accumulated OLF Years/10	-0.019	-0.019	-0.034
	(0.034)	(0.033)	(0.035)
Schooling * Tenure Years/10		0.007	
		(0.005)	
AFQT * Work Experience/10			0.025
			(0.007)***
Observations	33,707	33,181	31,672
R-squared	0.206	0.210	0.215
Tenure	No	Yes	No
Other controls:	Cubic Polynomial of Work Experience, Accumulated OLF/Unemployment/Military Years; Uncounted Years; and Years Dummies		

*** p<0.01, ** p<0.05, * p<0.1

White/Huber standard errors clustered at the individual level are reported in parentheses.

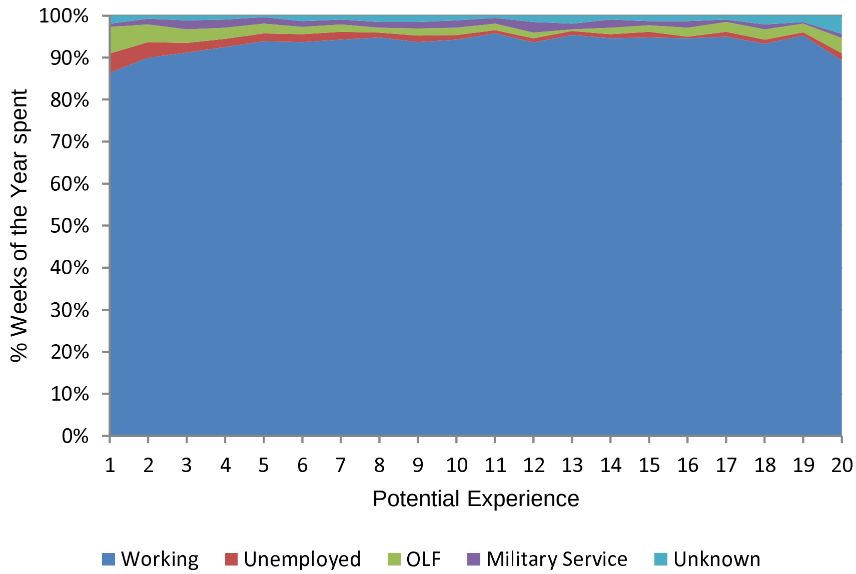
Note: AFQT is normalized to have a standard deviation of 1. Difference in the number of observations between models (1) , (2) and (3) is due to 526 observations of individuals with missing tenure and 1,545 observations of individuals with missing AFQT information.

Figure 1: Employment Attachment over the Life-Cycle - High School Graduates



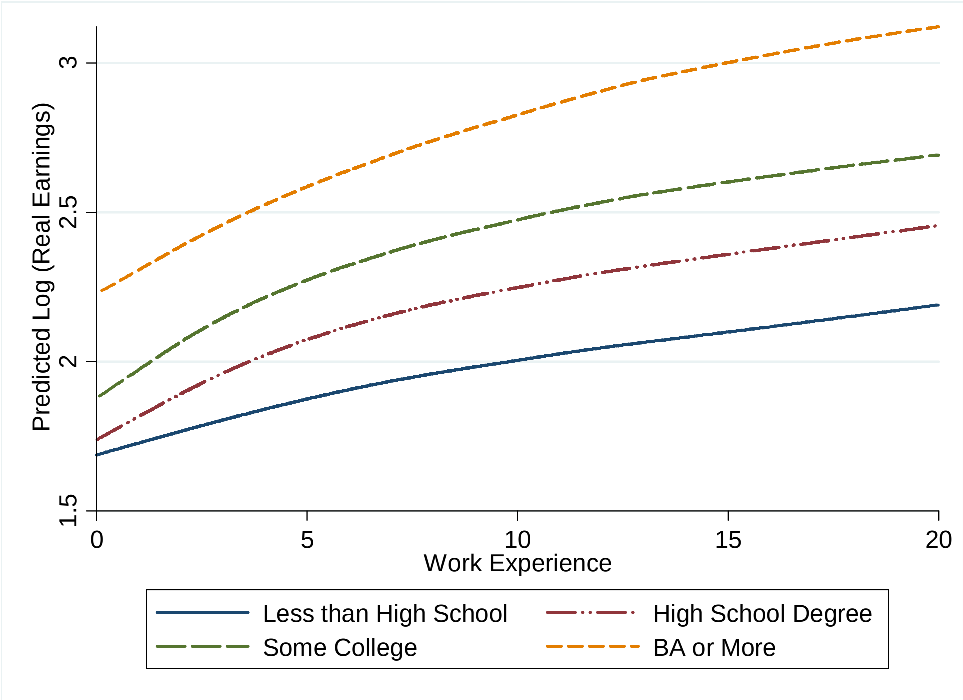
Note: Sample is restricted to observations after an individual left school. Weeks spent in each labor status are constructed using year aggregation of the week-by-week records.

Figure 2: **Employment Attachment over the Life-Cycle - Bachelor or More Graduates**



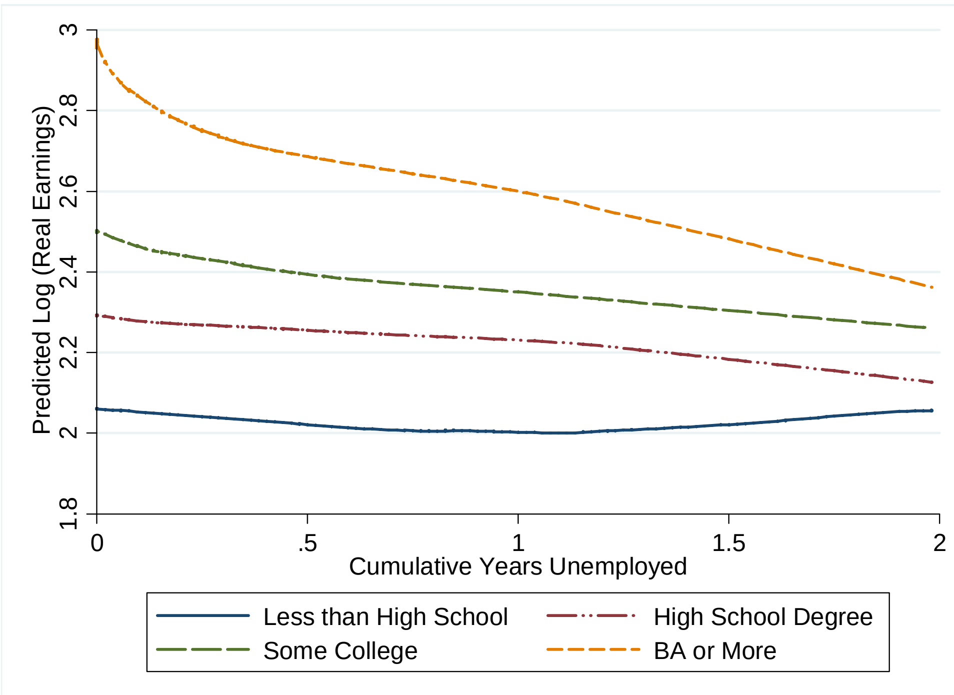
Note: Sample is restricted to observations after an individual left school. Weeks spent in each labor status are constructed using year aggregation of the week-by-week records.

Figure 3: **Log Earnings - Work Experience Profile**



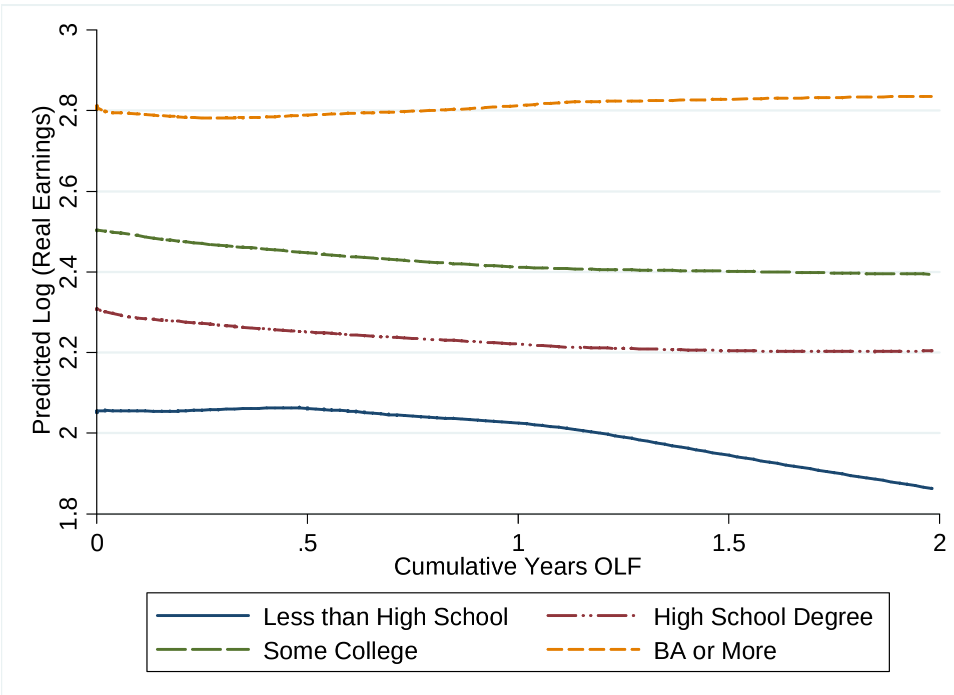
Note: The lines plot the predicted values from a locally weighted regression of log hourly earnings on work experience using a 0.5 bandwidth by each educational group. See section 3.2.2 for details.

Figure 4: Log Earnings - Cumulative Years Unemployed Profile



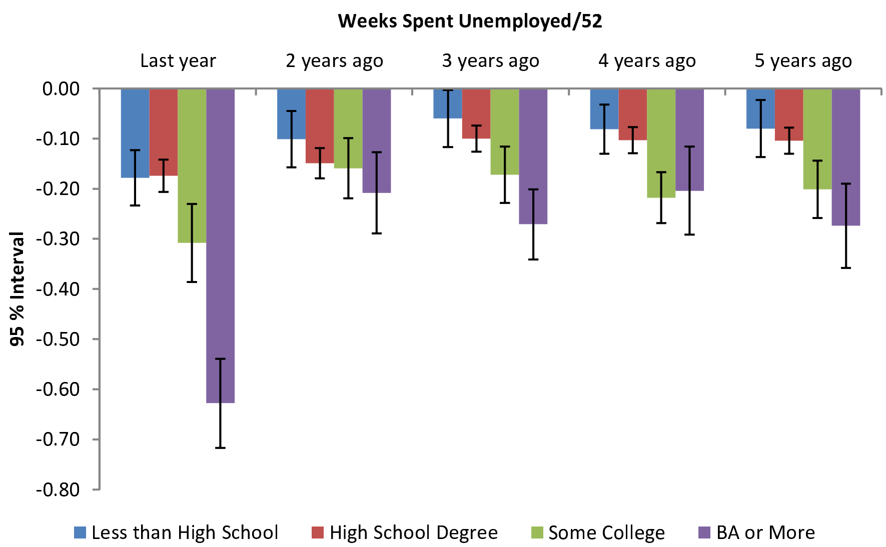
Note: The lines plot the predicted values from a locally weighted regression of log hourly earnings on cumulative years unemployed using a 0.25 bandwidth by each educational group. See section 3.2.2 for details.

Figure 5: Log Earnings - Cumulative Years OLF Profile



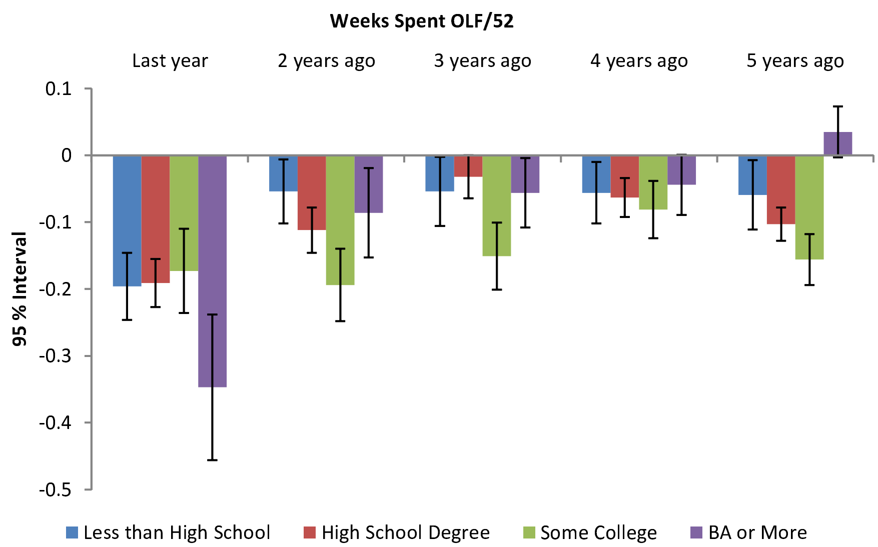
Note: The lines plot the predicted values from a locally weighted regression of log hourly earnings on cumulative year OLF using a 0.25 bandwidth by each educational group. See section 3.2.2 for details.

Figure 6: **The Effect of Unemployment on Earnings by Timing of Unemployment**



Note: Each bar represents the effect of weeks unemployed in each of the past 5 years conditional on weeks unemployment in the other 4 years. The model is estimated by linear least squares. The controls used are OLF periods, cubic polynomial of work experience, cumulative years military service; uncounted years, and years dummies. Confidence intervals are calculated using White/Huber heteroscedasticity standard errors cluster at the individual level. See section 3.2.3 for details.

Figure 7: **The Effect of OLF on Earnings by Timing of OLF periods**



Note: Each bar represents the effect of weeks OLF in each of the past 5 years conditional on weeks OLF in the other 4 years. The model is estimated by linear least squares. The controls used are unemployment periods, cubic polynomial of work experience, cumulative years military service; uncounted years; and years dummies. Confidence intervals are calculated using White/Huber heteroscedasticity standard errors cluster at the individual level. See section 3.2.3 for details.